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Research Article

ADAPTIVE- NEURO FUZZY SYSTEM AND VOLTAGE PROFILE CHARACTERISTICS EXTRACTION USING WAVELET ANALYSIS BASED SYSTEM FOR VOLTAGE STABILITY IN POWER NETWORKS

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ABSTRACT
The power network is the biggest machine made by human. The online monitoring and control of voltage stability has important role in security of power network. Modern networks have numerous sections and nonlinear devices. Therefore these modern networks act in their boundary of stability margins. In this situation, the online voltage stability monitoring and controlling will has high importance. This study presents a new technique to monitor and estimate the voltage stability margin using wavelet analysis and fuzzy rules. The proposed method has two main sections: the wavelet analysis section and adaptive neuro-fuzzy inference system (ANFIS) section. In the proposed method, voltage profile is used as the primary input. Based on the information achieved by voltage profile, the voltage stability margin will be estimated. The wavelet transformation is used to extract the most important information of original signal and the ANFIS section is used to estimate the voltage stability margin to evaluate the performance of proposed system, we used real world power network that place in United States. The simulation results show that the proposed method has high accuracy in estimating of voltage stability margin.

Keywords: *ANFIS, Wavelet Analysis, Approximation, Voltage, Stability*

INTRODUCTION
In last decade, new power system networks tend to act near to stability margins due to restructuring, open financial market and competition issues. Voltage instability and low voltage profile have significantly become a dramatic risk for secure performance of electric power networks. In the massively loaded high power networks, the events leading voltage distortion and low voltage profile cause to progressive subtraction in node voltage amplitude that can result in power system islanding and blackout situation. In these situations, real time voltage security investigation to preserve ideal amount of voltage security margin is a important necessary for maintaining power network safety. Numerous main voltage break up events resulted in vast blackouts (Khatua & Yadav, 2015). Several of these breaks up phenomena were studied in France, Italy, Sweden, Germany, China and the USA (Padma, 2015).
In last decades, artificial neural network has been applied successfully in many areas. The artificial neural network has been applied in power networks to detect the type of occurred fault in underground cables, detect the occurred faults in induction motor stator windings and many other applications. The artificial neural network has many types such multi layer Perceptron neural networks (MLPNN), radial basis function neural networks (RBFNN), probabilistic neural network (PNN), Elman neural network and so on. In artificial neural network, the radial basis function neural networks have good capabilities in function approximations and pattern recognition. In last year's, there are numerous studies about the real time voltage stability monitoring and controlling, investigating the properties of artificial neural networks for conjecturing mathematical relationship among voltage stability margins and the measurable power network system variables. In reference (Javan *et al.*, 2013) a new technique based on fast voltage and line-flow contingency screening applying an improved RBFNN and winner-take-all neural network is proposed to test if the power network system is safe under normal operating situations. In reference (Varshney *et al.*, 2012) a mixture safety investigation method using cascade ANN composed by a integrating of one screening section and two ranking section is introduced. In reference (Devaraj and Preetha, 2011) an intelligent system based on RBFNN with decreased input vector features is applied for approximate power network system voltage stability margin amount under contingency situation.

In reference (Cai and Erlich, 2015) a new method is introduced for power system dynamic voltage stability investigation based on the MIMO transfer function that is described the critical bus voltages as output sand possible control parameters as the input vector. The dynamic voltage stability investigation is performed based on the modal studies. In reference (Vakil and Razmi, 2008) a new technique based on a modular artificial neural networks is proposed for dynamic voltage stability investigation by establishing a straight mapping among operating terms and the dynamic VSM criteria of individual nodes. In reference (Chakrabarti, 2008), by applying artificial neural networks and a regression approach for choosing learning feature of artificial neural networks, a method is introduced for real time voltage stability assessment. Vital features for learning artificial neural networks are chosen by cause of the sensitivities of the voltage stability limits with compared to the input vector by the regression approaches. In reference (Jaim *et al.*, 2003), the supervised and unsupervised learning algorithms are used to radial basis function neural networks in order to decline the quantity of artificial neural networks needed for voltage contingency monitoring and hierarchy. In radial basis function neural networks, the number of radial basis function and spread of radial basis functions have vital figure in networks performance. Therefore these parameters must be selected carefully.
The wavelet analysis is a new method that has been successfully applied in many areas such as medical, communication, control, civil engineering and many other fields. In this paper we used wavelet transform to extract the effective features of unprocessed voltage profile signal. The proposed method used ANFIS system to approximate the final voltage stability margin based on wavelet transform outputs. The details of proposed method are described in section four. The wavelet transform is introduced in next section. In third section, the ANFIS concept is presented. The computer simulations are presented in section four. Finally the fifth section concludes the study.

Wavelet Analysis

Feature extraction has vital figure in estimation problems. In the proposed method, we used wavelet transformation to extract important features of voltage profile. There are some information such as load level, power factor and power loss in power lines in voltage profile. The voltage profile is useful to estimate the level of voltage stability margin. In the proposed method, we used approximation coefficients of wavelet transformation to estimate the voltage stability margin (Paras & Vipin, 2015).
Wavelet analysis retains the time variable facts in the original signal. The wavelet transformation leads to achieve the frequency information of original signal. This transformation permits frequency analysis of original signal. In this procedure, the proper selection of wavelet mother function, the level of decomposition and order of wavelet transformation have vital role. Therefore this selection must be done carefully and based on extensive simulations. In wavelet analysis, the original signal decompose to approximation and detail sections. The approximation section shows the main part of signal. The details section shows the noise and external components that added to original signal. The main procedure of wavelet transformation is illustrated in figure 1.

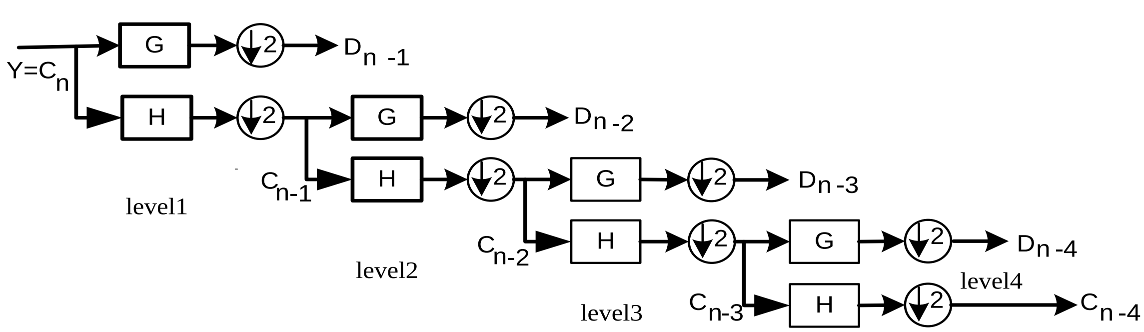

Figure 1: Multi resolution decomposition of signal Y

The level of decomposition is selected by trial and error. Based on the obtained results, the level of decomposition must be selected. In this paper, we used approximation coefficients of wavelet transformation. The multi-resolution wavelet analysis generates a package of the mathematical theory to define a function by using of projection onto a home tail of approximation spaces, where the wavelet coefficients will be used as the parameter that defines where the information may be purred. This transformation primary proposed by Mallet as an powerful and practical filtering method. The primary step of decomposition procedure will gain the 1st level of approximation coefficients that if decomposed will give the second level of approximation and can continue. So on. The mathematical calculation of wavelet transformation is as follow:

$$\phi(t) = \sum_{j,n} m(j,n)\psi_{j,k}(t) \tag{1}$$

Then we will have:

$$f(t) = \sum_{t} c_j(n)\phi_{j,t} + \sum_{t} d_j(t)\psi_{j,n} \tag{2}$$

The first sum in the above mentioned equation is the approximation coefficients and the second part is the details coefficients that removed during it. The approximation coefficients will be shown by c_j and the details coefficients will be shown by d_j at each level of decomposition procedure.

$$c_{j-1}(t) = \sum_{n} m(n-2t)c_j(n) \tag{3}$$

$$d_{j-1}(t) = \sum_{n} g(n-2t)c_j(n) \tag{4}$$

With

$$g(t) = (-1)^t m(1-t) \tag{5}$$

In this procedure, G is a low-pass filter and H is a high-pass filter. The mathematical representation of this transformation is as follow:

$$G\{a_t\} = \sum_{n} g(t-2n)a_t \tag{6}$$

$$H\{a_t\} = \sum_{n} m(t-2n)a_n \tag{7}$$

$$c_{j-1}(t) = H\{c_j\} = H \times c_j \tag{8}$$

$$d_{j-1}(t) = G\{c_j\} = G \times c_j \tag{9}$$

ANFIS

The ANFIS shows effective neural network way for the solution of function estimation, pattern recognition, fault detection and forecasting problems. Information driven way for the synthesis of ANFIS systems are usually based on clustering a training dataset of numerical samples of the vague function to be approximated or forecasted. The ANFIS systems have been productively used to pattern recognition tasks, nonlinear control systems, fault detection problems and many other applications (Karthika & Paresh, 2015). In adaptive neuro-fuzzy inference systems, the fuzzy rules are extracted by clustering the input data. In the following sections the main steps of ANFIS system are presented.

For simplicity, it is considered that the fuzzy inference network under investigation has two inputs signal and one output signal. The rule base includes two main fuzzy if>then rules of Takagi and Sugeno's (TS) type that defined as following form:

If x is A and y is B .... then z is f(x,y)

That A and B are the fuzzy collections in the oral forms and z=f(x,y) is a sharp math function in the consequent form. f(x,y) is traditionally a polynomial function for the input parameters x and y. But it may also be any other favorite function that may relatively define the output of the problem within the fuzzy space as predetermined by the oral rules. When f(x,y) is a fixed function, a zero order TS fuzzy network is composed, which can be assumed to be a special case of Mamdani fuzzy inference network, where each oral rule chain is determined by a fuzzy singleton. If f(x,y) is taken to be a first order polynomial function a first order TS fuzzy network is composed. For a first order two-rule TS network fuzzy system, the two oral rules can be defined as follow:

First rule : *If* x is A_1 and y is B_1 then $f_1=p_1x+q_1y+r_1$

Second rule: *If* x is A_2 and y is B_2 then $f_1=p_2x+q_2y+r_2$

In this study, type-3 ANFIS network proposed by TS is applied. In TS network, the output of each oral rule is a linear mixture of input parameter summed by a fixed condition. The latest output signal is the weighted average of each oral rule's output. The main structure of ANFIS system is illustrated in figure 2.

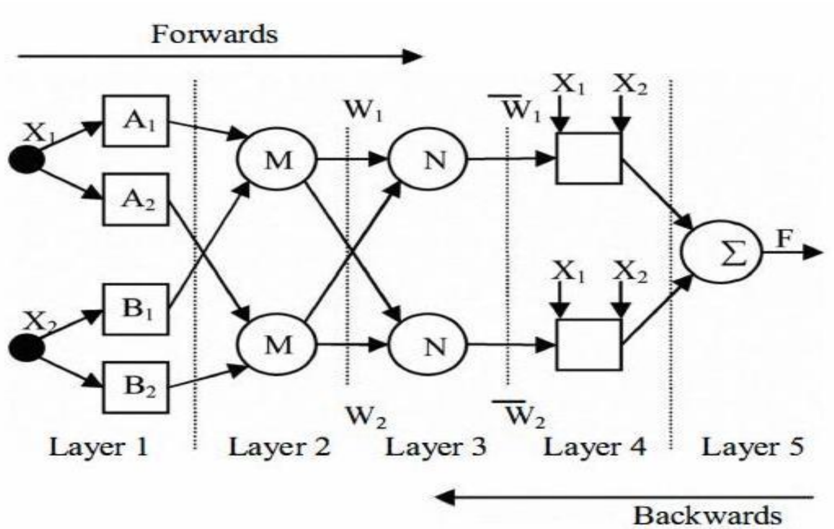

Figure 2: The main structure of ANFIS

The single layers of this ANFIS network are defined as follow:

The first layer: Each spot *k* in the first layer is adaptive with a node predetermined function:

$$O_k^1 = \mu_{A_k}(x) \qquad (10)$$

That x is the input to spot k, A_k the linguistic parameter combined with this spot function and μ_{A_k} is the membership function of A_k . Often $\mu_{A_k}(x)$ is selected as:

$$\mu_{A_k}(x) = \frac{1}{1+[(x-c_k/a_k)^2]^{b_k}} \qquad (11)$$

Or

$$\mu_{A_k}(x) = \exp\left\{-(\frac{x-c_k}{a_k})^2\right\} \qquad (12)$$

that x is the input signal and $\{a_k, b_k, c_k\}$ is the premise variables package.

Second layer: Every spot in second layer is a constant node that computes the firing force w_i of aoral rule. The output signal of per spot is the multiplication of all the incoming vectors to it and is defined by:

$$O_k^2 = w_k = \mu_{A_k}(x) \times \mu_{B_k}(x) \quad , \quad k=1, 2 \qquad (13)$$

Third layer: Each spot in this layer is a constant spot. Per *k*th spot computes the ratio of the kth rule's firing force to the adding of firing force of all the oral rules. The output vector from the kth spot is the normalized firing force defined by:

$$O_k^3 = \overline{w} = \frac{w_k}{w_1 + w_2} \quad , \qquad k=1,2 \qquad (14)$$

Forth layer: Each spot in the forth layer is an adaptive spot with a spot function described by

$$O_k^4 = \overline{w_k}\, f_k = \overline{w_k}(p_k x + q_k y + r_k) \qquad (15)$$

That $\overline{w_k}$ is the output vector of third layer and $\{p_k, q_k, r_k\}$ is the chain variable package.

Fifth layer: The fifth layer comprises of just one constant spot that computes the overall output vector as the addition of all incoming vector signals, that:

$$O_k^5 = overall\ \text{output} = \sum_i \overline{w_k}\, f_k = \frac{\sum_k w_k f_k}{\sum_k w_k} \qquad (16)$$

MATERIALS AND METHODS

Proposed Method and Simulation Results

Proposed Method

In this paper an intelligent hybrid system is proposed for voltage stability margin estimation. The proposed method has two main sections: the wavelet analysis section and adaptive neuro-fuzzy inference system (ANFIS) section. In the proposed method, voltage profile is used as the primary input. Based on the information achieved by voltage profile, the voltage stability margin will be estimated. The wavelet transformation is used to extract the most important information of original signal and the ANFIS section is used to estimate the voltage stability margin. To evaluate the performance of proposed system, we used real world power network that place in united states.

In ANFIS, the type of membership function, fuzzy inference system, vector of radius, clustering algorithm and dimension of input vector have vital role in its final performance. Therefore in this study, these parameters have been selected based on trial and error and after extensive simulations. The main structure of proposed method is illustrated in figure 3.

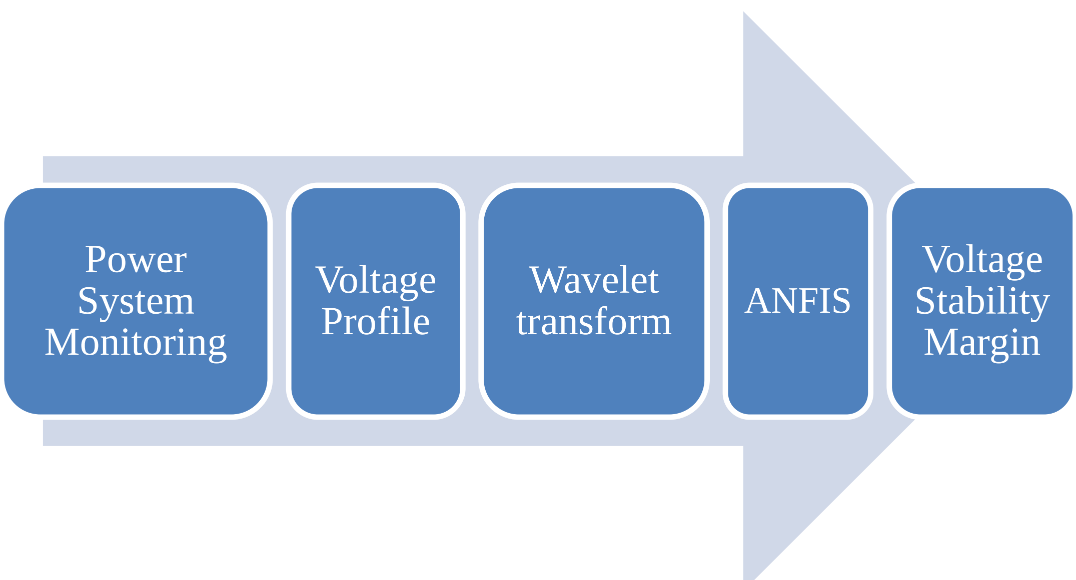

Figure 3: The main structure of proposed method

In the proposed method, at per operating prompt, all synchronously measured node voltage values constitute power system voltage profile for safety investigation.

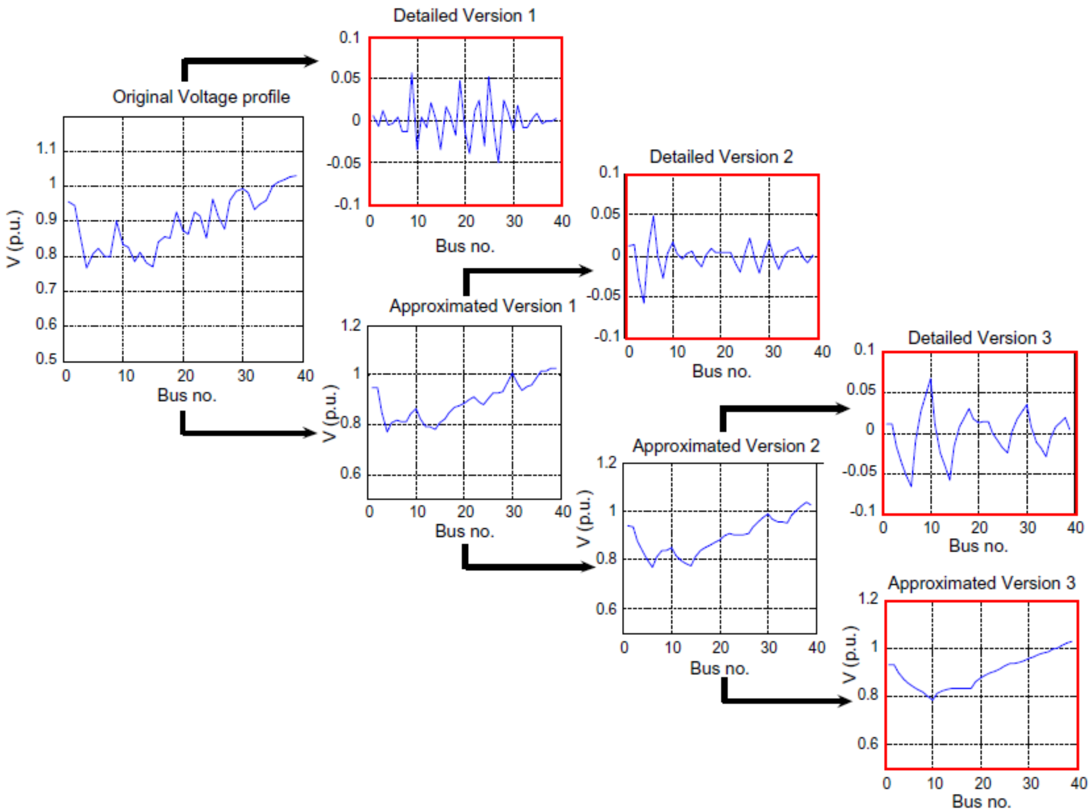

Figure 4: The feature extraction procedure using wavelet transform

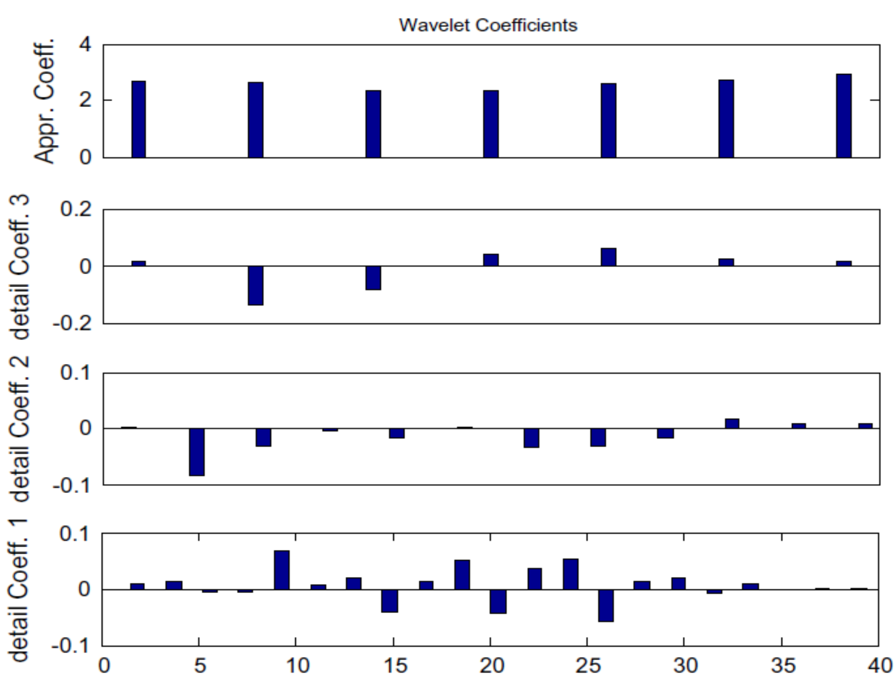

Figure 5: Coefficients of a sample voltage profile vector

Power system voltage profile is a character of power network including the impact of all network features such as load amount, load-generation model, reactive power level and its compensation by shunt capacitors and network configuration on the system safety.
Therefore, power system voltage profile is assumed as original input for approximating power system stability margin. In the computer simulation, we used 25- node and 14-node IEEE system that located in United States.
In the proposed method, we used wavelet transform to extract the best and effective features of voltage profile. This procedure is shown in figures 4 and 5. The selected effective features used as ANFIS input to estimate the voltage stability margin.
The output vector of ANFIS is power network voltage stability margin including the interval of power network operating situation to the point of voltage break up in condition of active power load amount. Generally speaking, the introduced technique provides a instrument for online approximation of voltage stability margin.

RESULTS AND DISCUSSION

Simulation Results

In the introduced voltage stability margin estimation method using ANFIS, a voltage stability analyzer fuzzy system is composed and learned. The input vector of proposed method include of best features of the power system voltage profile.
At per prompt of power network operation consisting static or quasi dynamic situations, by synchronized sampled variables of voltage profile and extracting its effective properties using wavelet transform, ANFIS can to estimate the voltage system stability margin. The test systems are shown in figures 6 and 7. These systems have 14 and 25 terminal and located at united states.

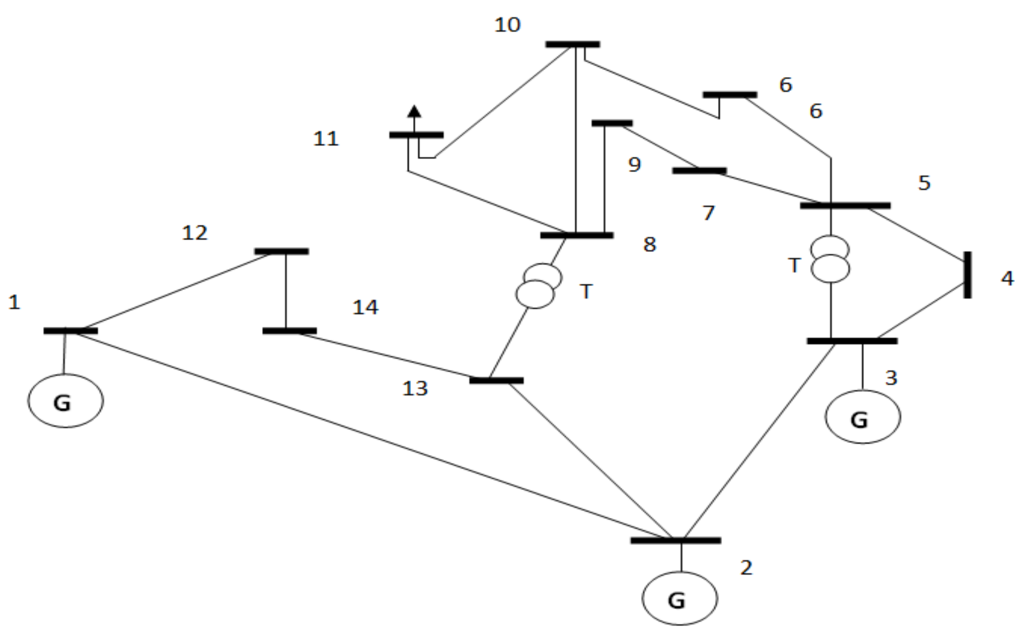

Figure 6: The 14-node test power network

In the proposed method we used 60% of data to train the ANFIS and the remaining to evaluate the proposed system. Table 1 shows the obtained results. In the proposed method, we used Gaussian membership function and TS fuzzy inference system. In the test section, the root mean square error is used as the performance index. It can be seen that the proposed method ha good performance. The figures 8 and 9, show the voltage profile of test systems.

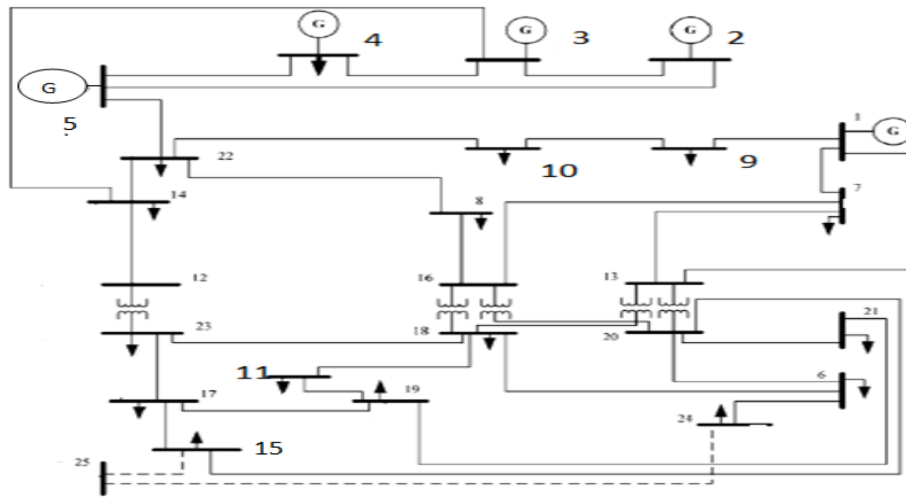

Figure 7: The 25-node test power network

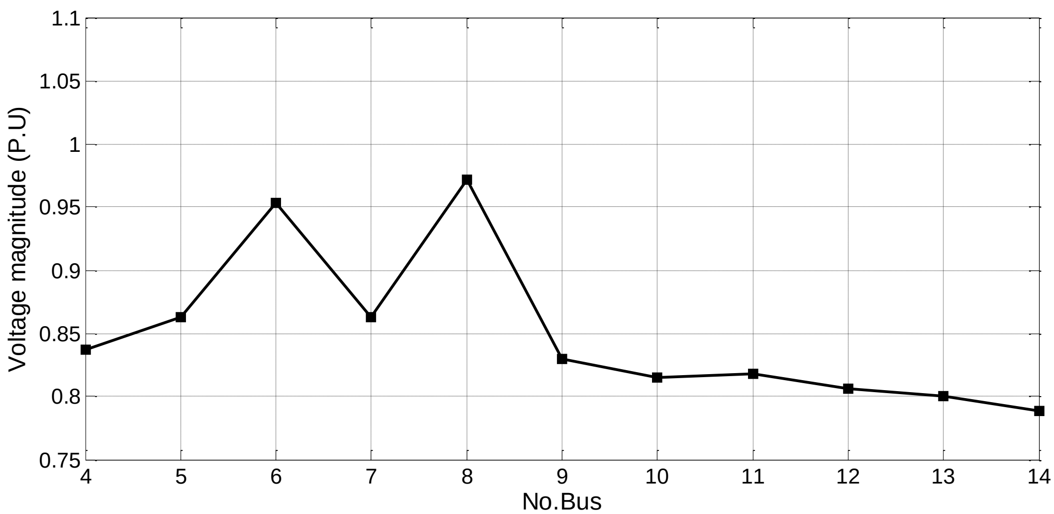

Figure 8: The voltage profile of test system (14- node)

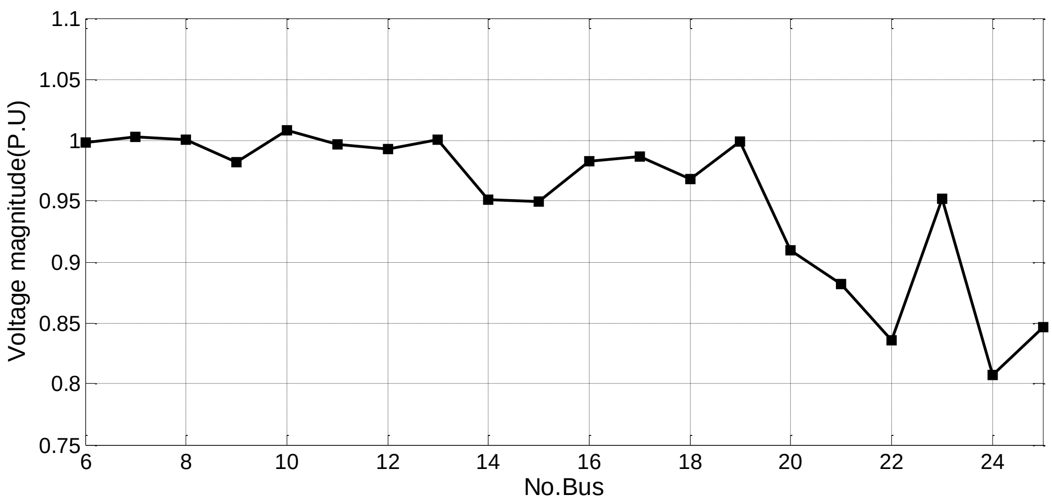

Figure 9: The voltage profile of test system (25- node)

Table 1: The obtained results using the proposed method

	Membership function	Fuzzy motor	Radii	RMSE (MW)
14- bus system	Gaussian	Takagi- Sugeno	0.38	47
25- bus system	Gaussian	Takagi- Sugeno	0.74	83

As mentioned, in ANFIS training the radii has high effect on its performance. The value of radii has no linear relation to performance of ANFIS. Therefore this parameter must be selected based on trial and error. In table 2, the effect of radii variation is investigated on 25-bus system.

Table 2: Performance of proposed system and radii variation investigation

radii	RMSE (MW)	No. rules
0.1	95	16
0.2	88	9
0.3	91	6
0.4	90	5
0.5	92	**5**
0.6	93	4
0.7	89	3
0.8	91	3
0.9	90	2
1	93	2

In next figures the variation of radii and number of rules are investigated. It can be seen that there are no straight relation between the radii and number of fuzzy rules. When radii has little value, the number of fuzzy rules is high and vice versa. Therefore the value of radii must be selected carefully.

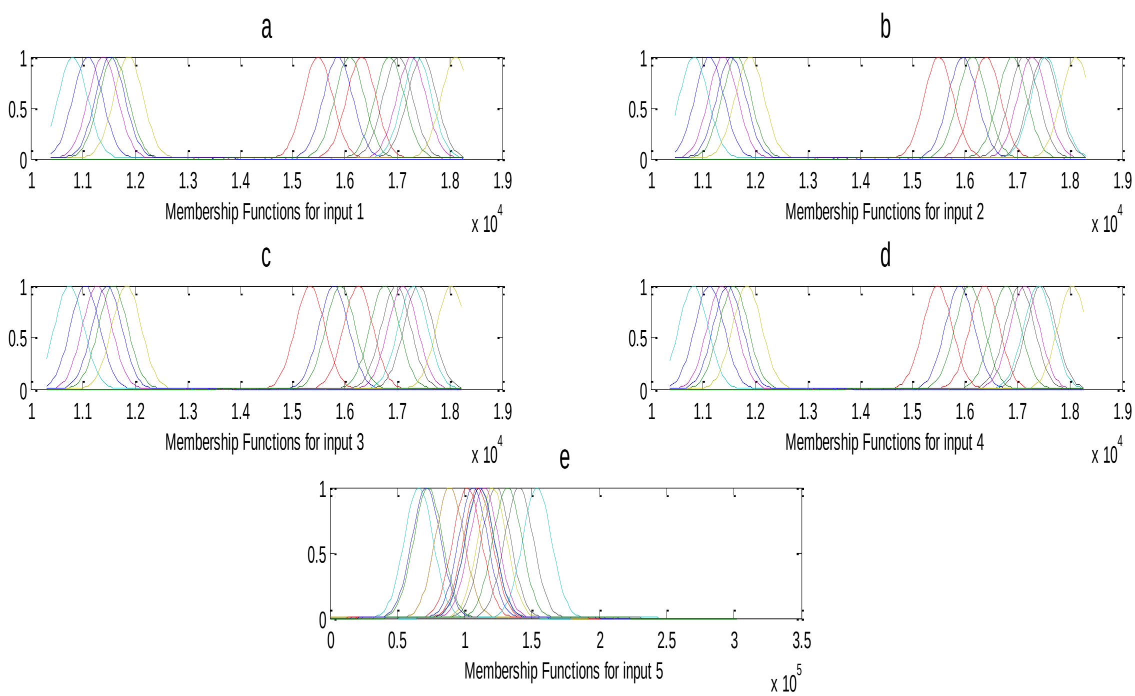

Figure10: Membership functions for Radii=0.1

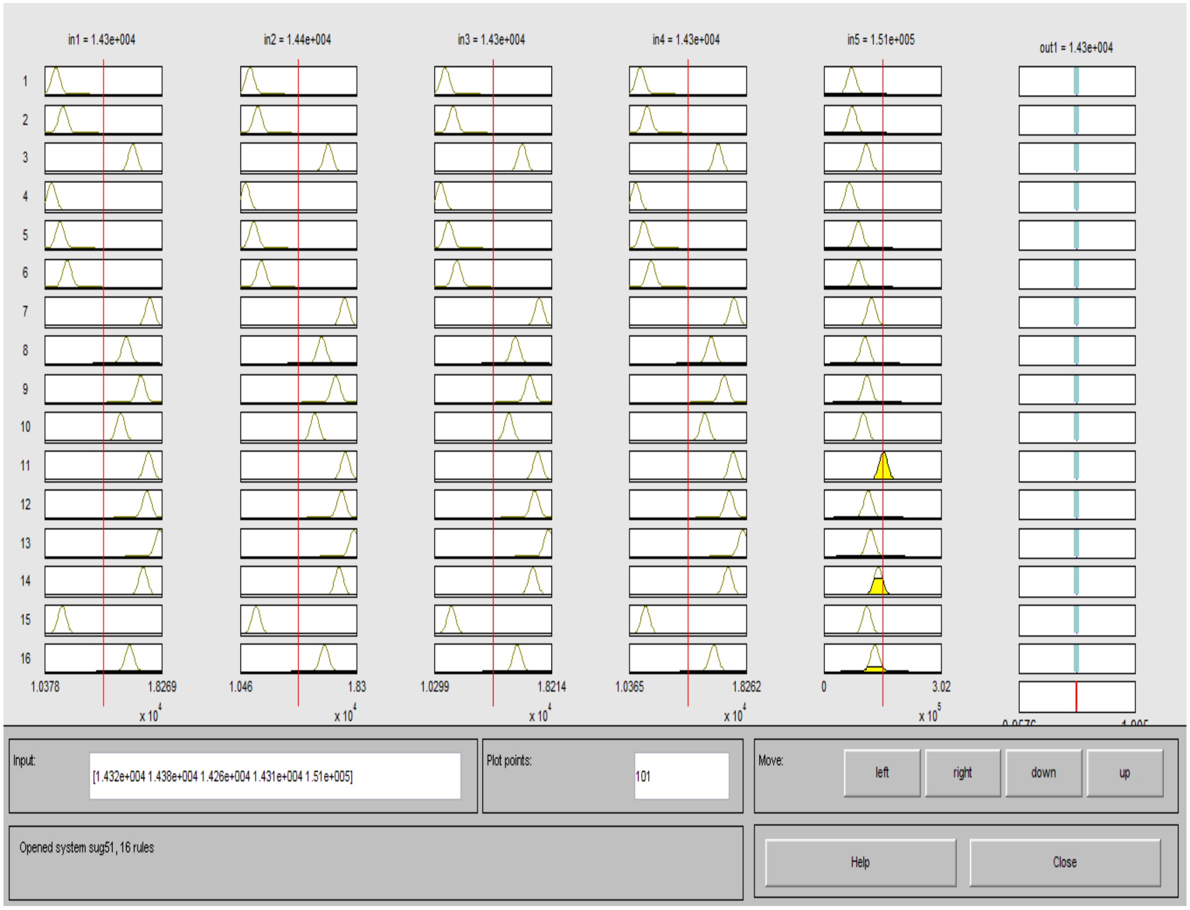

Figure 11: Fuzzy rules for raddi =0.1

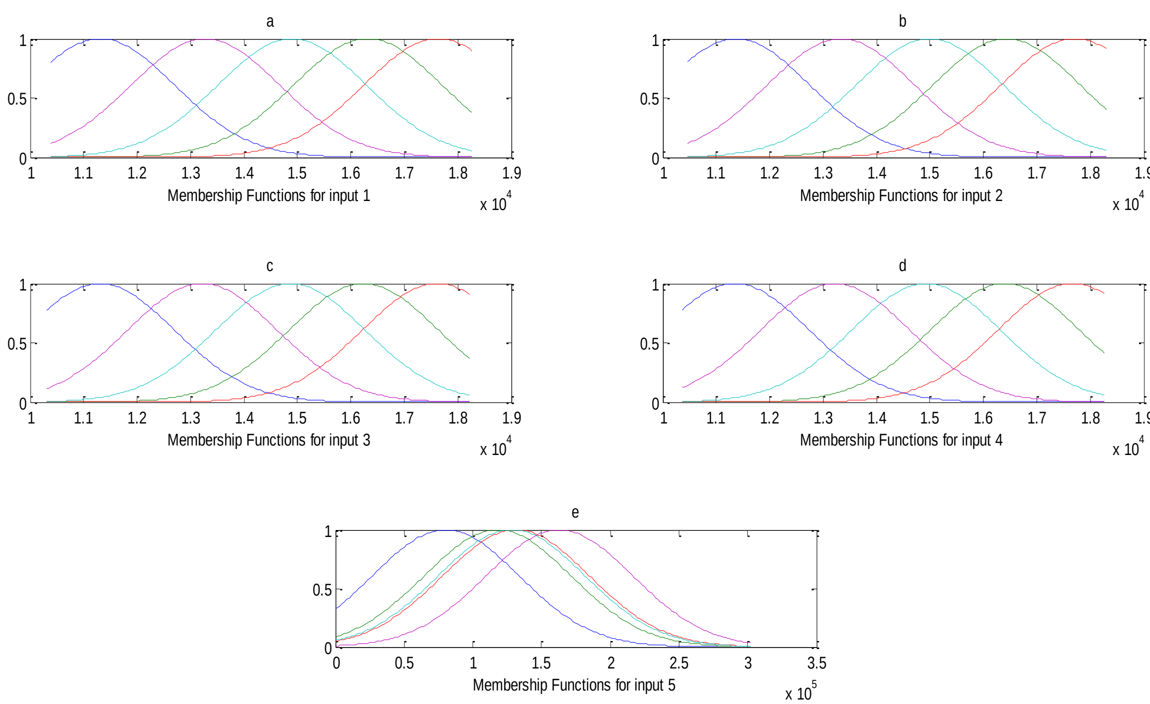

Figure12: Membership functions for Radii=0.5

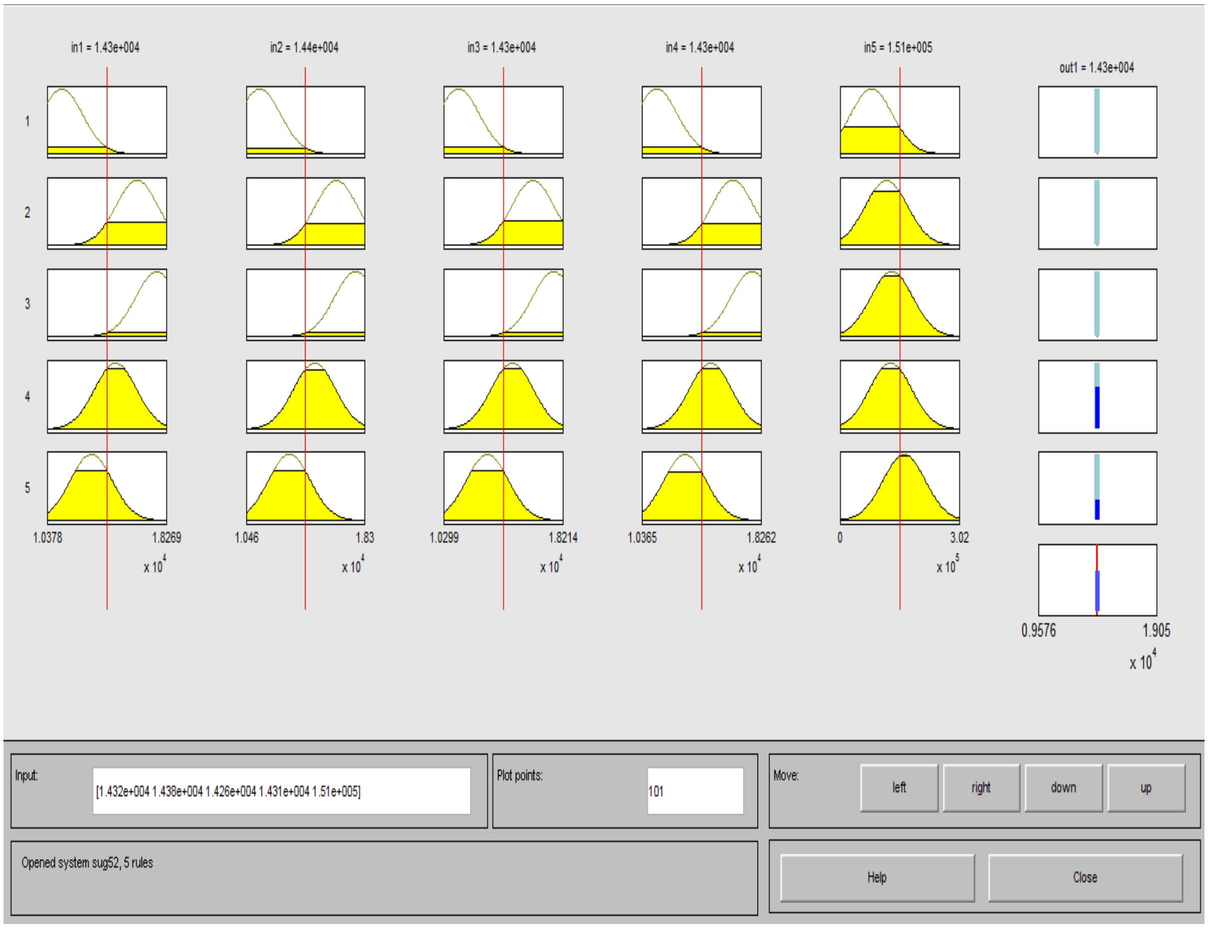

Figure 13: Fuzzy rules for radii=0.5

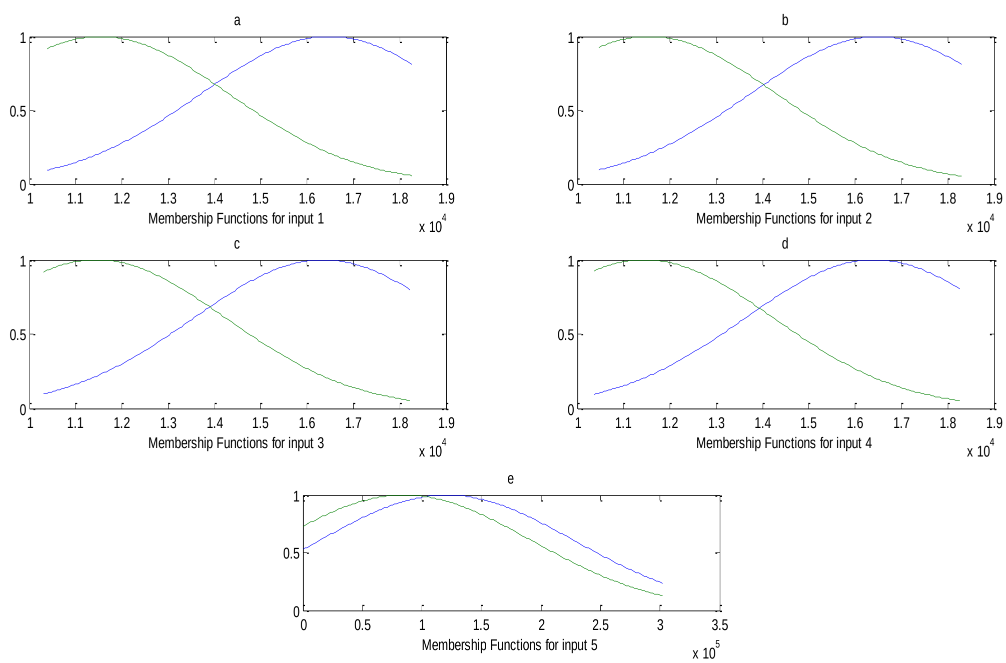

Figure 14: Membership functions for Radii=1

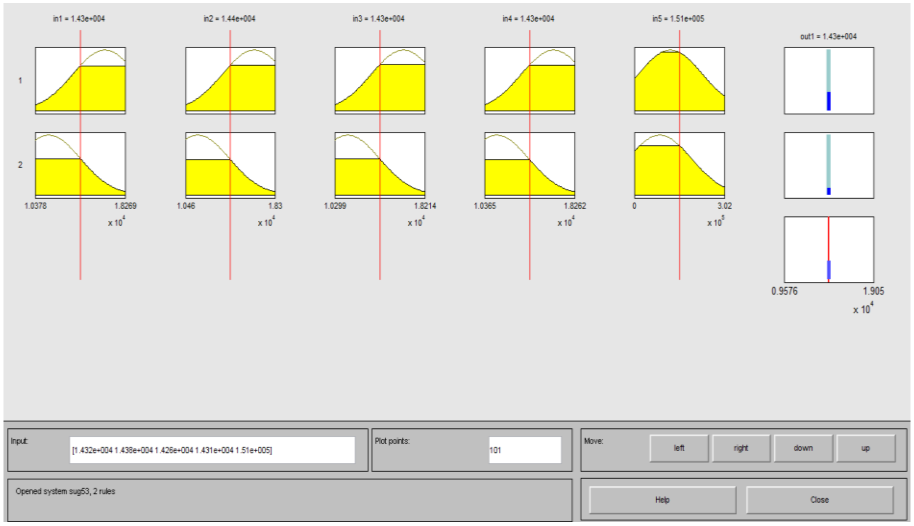

Figure 15: Fuzzy rules for radii=1

Table 3: Mother wavelet effect on proposed method performance

Mother wavelet	RMSE (MW)
Mexican hat	83
Db2	84
Db3	84
Db4	85
Db5	84
Db6	84
Db7	84
Db8	84
Db9	84
Db10	84
Coif2	84
Coif3	84
Coif4	84
Coif5	86
Sym2	84
Sym3	85
Sym4	84
Sym5	84
Sym6	85
Sym7	85
Sym8	85
Bior1.3	86
Bior1.5	84
Bior2.2	84
Bior2.4	84
Bior2.8	84
Bior3.1	84
Bior3.3	85
Bior3.5	85
Bior3.7	84
Bior3.9	84
Bior4.4	84
Bior5.5	84
Bior6.8	84

In order to in investigate the effect of mother wavelet, we done some simulations. In this simulation, we used several mother wavelet. It can be seen from table 3, that the wavelet transform with Mexican hat has better performance rather than others.
In next experiment, we investigate other tools for estimate of voltage stability margin such as MLP neural network, radial basis function neural network, probabilistic neural network and Elman neural network. The obtained results are listed in table 4. In this experiment we used Mexican hat mother wavelet. Also the parameters and structure of neural networks are selected by trial and error and based on best results.

Table 4: Performance of ANNs

ANNs type	Parameters	RMSE (MW)
MLP	2 layer, 20 neurons in hidden layer	89
PNN	Spread= 2	94
RBF	Spread= 3, Number of radial functions= 50	84
Elman	18 neurons in hidden layer	85

Conclusion

In this paper an intelligent hybrid system is proposed to estimate the voltage stability margin. The proposed method act base on capability of wavelet transform and ANFIS. The proposed method tested with two real world IEEE standard networks. The simulation results show that the proposed method can estimate the voltage stability margin with acceptable error. The parameters of ANFIS such as membership function type, radii and fuzzy motor selected by trial and error. Also the effect of mother wavelet investigated and Mexican hat mother wavelet selected as best mother wavelet. In next experiment the performance of proposed system is compared with neural networks. The obtained results show that the ANFIS has better performance rather than ANNs.

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